Taylor & Francis
Taylor & Francis Group

Mechanics Based Design of Structures and Machines

An International Journal

ISSN: 1539-7734 (Print) 1539-7742 (Online) Journal homepage: www.tandfonline.com/journals/lmbd20

Regression surrogate modeling for structural optimization of rear underrun protection device (RUPD) for trucks

Sachin M. Bhosle, Sangram S. Bhosale, Shrikant C. Mahadik & Sunil M. Pondkule

To cite this article: Sachin M. Bhosle, Sangram S. Bhosale, Shrikant C. Mahadik & Sunil M. Pondkule (2026) Regression surrogate modeling for structural optimization of rear underrun protection device (RUPD) for trucks, Mechanics Based Design of Structures and Machines, 54:1, 2627622, DOI: 10.1080/15397734.2026.2627622

To link to this article: https://doi.org/10.1080/15397734.2026.2627622

Published online: 03 Mar 2026.

MECHANICS BASED DESIGN OF STRUCTURES AND MACHINES
2026, VOL. 54, NO. 1, 2627622
https://doi.org/10.1080/15397734.2026.2627622

Regression surrogate modeling for structural optimization of rear underrun protection device (RUPD) for trucks

Sachin M. Bhosle[a,b], Sangram S. Bhosale[a,b], Shrikant C. Mahadik[a,b], and Sunil M. Pondkule[b,c]

[a]Mechanical Engineering, Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology, Baramati, Maharashtra, India; [b]Mechanical Engineering, Savitribai Phule Pune University, Pune, Maharashtra, India; [c]Mechanical Engineering, Sharadchandra Pawar College of Engineering, Someshwarnagar, Maharashtra, India

ABSTRACT

This study presents a regression-based surrogate modeling framework for analyzing the quasi-static structural response of a truck rear underrun protection device (RUPD). Finite element data from five configurations are used to examine the effect of slot distance from the mounting plane (50–150 mm) as a single geometric parameter. Low-order polynomial surrogates are developed for von Mises stress, factor of safety (FoS), and mass, enabling interpolation between discrete designs. Results show a monotonic increase in FoS with slot distance; relative to the 125 mm reference, the maximum distance yields a 30.8% FoS increase and 25.7% stress reduction, at the cost of higher mass.

ARTICLE HISTORY
Received 7 December 2025
Accepted 29 January 2026

KEYWORDS
Surrogate model; regression; finite element; design optimization; factor of safety

1. Introduction

Rear underrun collisions between passenger vehicles and heavy commercial trucks remain a major global road-safety concern, frequently resulting in severe or fatal injuries due to intrusion of the smaller vehicle beneath the truck chassis (Brumbelow and Blanar 2012; Anderson et al. 2004; Bende and Gwehenberger 2005; Marine, Wirth, and Thomas 2002). Accident statistics from North America and Europe indicate that a substantial proportion of fatal rear-end crashes involve heavy vehicles, highlighting the critical role of effective and regulation-compliant rear underrun protection devices (RUPDs) (Atahan 2003; Joshi, Jadhav, and Joshi 2012; Sen et al. 2014). An RUPD functions as a structural barrier mounted at the rear of a truck to limit underride and reduce passenger-compartment intrusion during rear-end impacts (Rakesh, Singh, and Srinivas 2017; Trego et al. 2003; Brumbelow 2015). Figure 1A illustrates representative real-world collisions in which inadequate or absent RUPDs led to severe underride outcomes (Al-Bahash, Ansari, and Shah 2018).

In response to these safety challenges, regulatory frameworks such as UNECE R58, FMVSS, and AIS prescribe minimum strength, stiffness, and deflection requirements for RUPDs, motivating sustained research into improved structural design, materials, and geometric configuration (European Commission 2022). Owing to the high cost and complexity of full-scale crash testing, finite element analysis (FEA) has become the primary tool for evaluating RUPD structural performance under standardized loading conditions (Park, Kim, and Lee 2019; Gupta, Sharma, and

CONTACT Sachin M. Bhosle Sachin.bhosle@vpkbiet.org Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology, Baramati, 413133, Maharashtra, India.
Communicated by Francisco Silva.

(A)

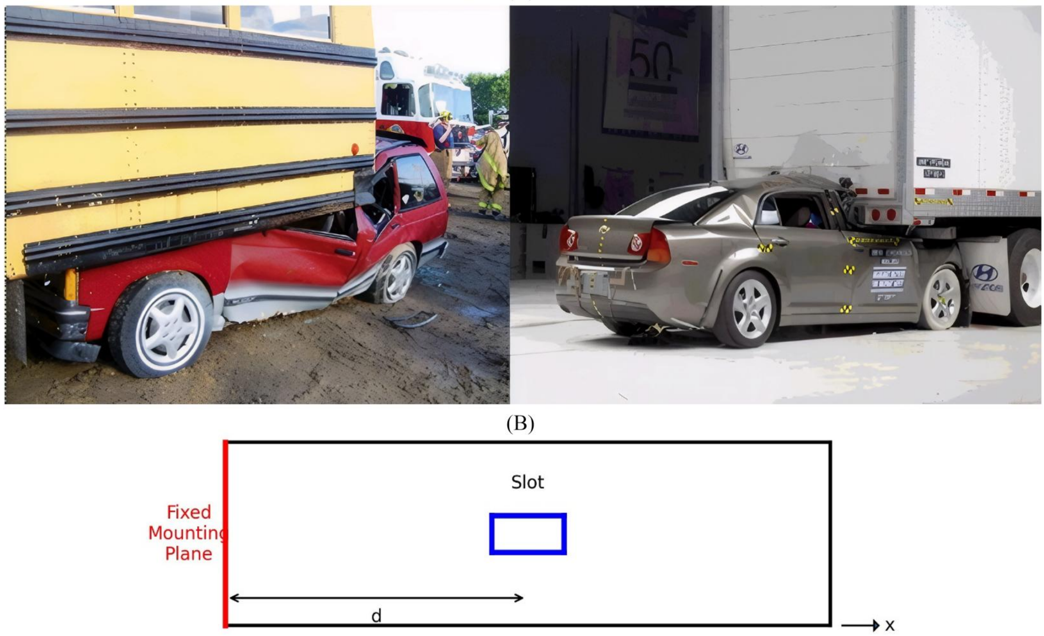

Figure 1. (a) Examples of real-world rear-end collisions showing severe passenger-car underride due to the absence or inadequacy of RUPD (Al-Bahash, Ansari, and Shah 2018). (b) Schematic illustration defining the slot distance *d* and the fixity constraint location.

Gupta 2020; Zhang, Li, and Sun 2021; Vats, Singh, and Sharma 2022; Kim, Park, and Wang 2018). Numerous studies have demonstrated that FEA provides reliable insight into stress distribution, deformation behavior, and load transfer mechanisms relevant to underride protection design and regulatory compliance (Jaiswal and Singh 2021; Li, Sun, et al. 2020; Wang, Li, and Yao 2022; Saini, Kumar, and Mehta 2023).

In the authors' prior work, a three-dimensional CAD model of a hollow-section RUPD cross-bar was developed in accordance with regulatory geometry constraints. The geometric configuration of the RUPD cross-bar considered in this study is illustrated in Figure 2. The model consists of a hollow rectangular section incorporating an internal slot geometry, which serves as the primary parametric feature investigated in the present analysis. The slot distance from the fixed mounting plane is varied systematically to evaluate its influence on stress distribution, factor of safety, and structural mass under quasi-static loading conditions. A mesh-convergence study identified a mesh-independent configuration (35,558 nodes and 20,651 elements), and linear-elastic ASTM A36 steel properties were applied. The initial design satisfied stress and displacement requirements, yielding a maximum von-Mises stress of 184.6 MPa and a factor of safety (FoS) of 1.35. Subsequent FE-based parametric evaluation identified the longitudinal position of the internal slot relative to the fixed mounting interface as a dominant geometric parameter influencing stress, FoS, and structural mass. Analytical surrogate exploration further indicates that FoS increases monotonically across the investigated slot-distance range, with the upper bound (150 mm) representing the analytical limit of the safety trend rather than an optimized design solution.

Although FE-based parametric studies provide high-fidelity structural insight, repeated simulations are computationally expensive and impractical for rapid design-space exploration. To address this limitation, surrogate modeling techniques have been widely adopted to approximate FE responses using computationally inexpensive analytical representations (Forrester, Sobester, and Keane 2008; Queipo et al. 2005; Santner, Williams, and Notz 2003; Lophaven, Nielsen, and

Søndergaard 2010; Haftka and Gürdal 2019). Such approaches enable efficient visualization of response trends, sensitivity assessment, and preliminary design screening without exhaustive FE recomputation (Razavi et al. 2012; Keshavarz, Dey, and Ulutan 2021; Mahdavi and Seyed-Esfahani 2020; Farrokh, et al. 2022; Li, et al. 2021). While advanced surrogate models such as Kriging, radial basis functions, and neural networks are commonly applied in high-dimensional or highly nonlinear problems (Shan and Wang 2010; Lyu, Khodadadi, and Luo 2021; Gohari and Kiani 2021; Farrokh and Khajepour 2022), low-order polynomial regression remains effective when structural responses are smooth, monotonic, and data availability is limited (Lyu, Khodadadi, and Luo 2021; Gohari and Kiani 2021). In such cases, polynomial surrogates offer transparency, numerical robustness, and reduced overfitting risk, making them particularly suitable for early-stage, physics-informed design studies.

Motivated by these considerations, the present work develops regression-based surrogate models using five high-fidelity FE configurations generated in the authors' earlier study. The surrogates analytically represent the relationship between slot distance and three structural response quantities: maximum von-Mises stress, factor of safety, and structural mass. Rather than seeking a non-intuitive geometric optimum, the objective is to demonstrate how a deliberately sparse FE dataset can be transformed into a continuous analytical representation of structural safety trends. This enables systematic interpretation of geometric sensitivity and comparative evaluation of intermediate configurations under simplified loading assumptions, without additional FE simulations.

The authors have previously contributed to computational mechanics and data-driven modeling of mechanical systems, including finite-element-based structural response analysis and regression-based surrogate modeling (Mahadik et al. 2025; Bhosle et al. 2025; Pondkule, Bhosle, and Mahadik 2026; Pondkule and Bhosle 2025). These studies provide the methodological foundation for the present work, particularly in integrating high-fidelity numerical simulations with interpretable regression frameworks for analytical design-space exploration.

Accordingly, this paper presents a rigorously constrained case study examining the effectiveness and practical limits of low-order polynomial surrogates for analytical trend interpretation in single-parameter structural design problems under extreme data scarcity. The contribution lies not in identifying a novel optimum, but in demonstrating how interpretable regression-based surrogates can support transparent evaluation of stress redistribution, safety-margin evolution, and mass sensitivity, while explicitly acknowledging the boundaries between interpolation, extrapolation, and physical predictability. Within this scope, the study positions polynomial surrogate modeling as a complementary analytical tool for early-stage structural assessment rather than a substitute for high-fidelity crash simulations or comprehensive optimization frameworks.

2. Materials and methods

This section describes the geometric parameterization, finite element modeling assumptions, and surrogate modeling framework adopted to evaluate the influence of slot distance on RUPD structural response.

2.1. RUPD geometry and CAD modelling

The rear underrun protection device (RUPD) geometry considered in this study complies with the dimensional requirements specified in UNECE Regulation R58 and AIS-069 and is representative of configurations commonly reported in recent structural safety studies (Kanyilmaz and Ozakgul 2021; Zhang, Wang, and Xu 2020; Zhou, Li, and Xu 2021). The CAD model, developed in the authors' prior work, consists of a hollow rectangular steel cross-bar with outer dimensions of 100 mm × 150 mm and an internal elongated slot measuring 50 mm × 80 mm. Hollow-section

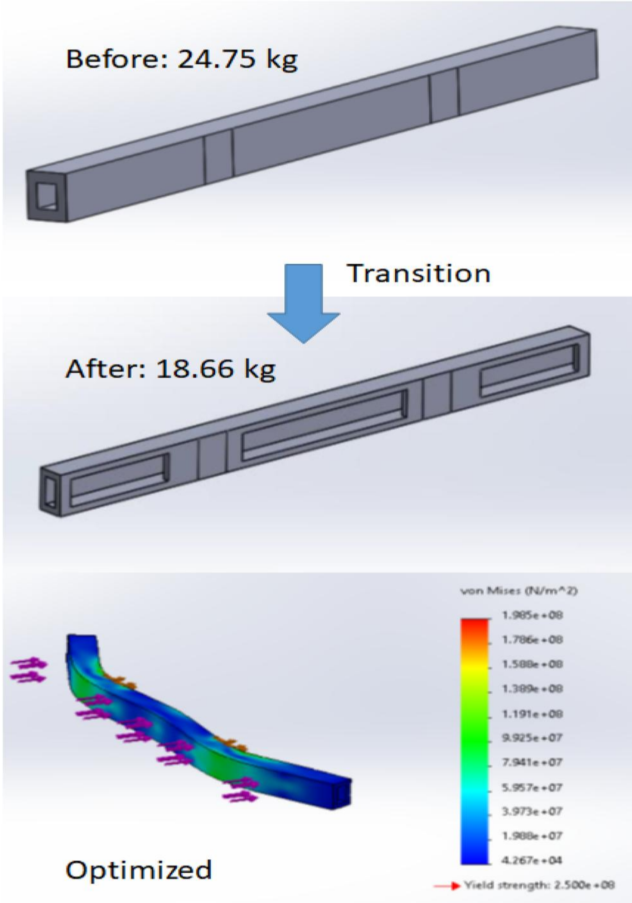

Figure 2. CAD model of the rear underrun protection device (RUPD) cross-bar showing the hollow rectangular section and internal slot geometry used for finite element analysis.

RUPD designs are widely adopted due to their favorable balance between bending stiffness and mass efficiency in protective structures (Jones et al. 2022; Alsaleh and Aljuaid 2021).

The total cross-bar length is 2,250 mm, satisfying standard truck-width constraints and mounting clearances. In the present study, the *fixity constraint* refers to the rear mounting interface of the RUPD assembly, where all translational and rotational degrees of freedom are constrained to represent rigid attachment to the truck chassis.

The geometric design parameter investigated is the *slot distance d*, defined as the longitudinal distance measured along the primary load-transfer axis of the RUPD beam from the fixed mounting plane to the centerline of the internal slot. This parameter governs the relative position of the material discontinuity with respect to the fixed boundary and influences local stress redistribution and bending response under applied loading. A schematic illustration defining the slot distance *d* and the fixity constraint location is provided in Figure 1B to ensure clarity and reproducibility.

To facilitate load and boundary condition assignment, the CAD geometry was partitioned to define five load-application regions and two support interfaces, following modeling practices reported in prior studies on underride protection and automotive safety structures (Al Batayneh, et al. 2022). The finalized CAD model was subsequently exported for finite element analysis.

2.2. Finite element Simulation setup

Finite element (FE) simulations were performed using SOLIDWORKS Simulation with tetrahedral solid elements. A sufficiently refined mesh is required to accurately capture stress gradients in thin-walled protective structures, particularly near fixed boundaries and geometric discontinuities. Consistent with recommendations from recent FE-based structural assessments of safety-critical automotive components (Prabhu and Kumar 2021; Li, Sun, et al. 2020; Aghdam and Ziaei-Najafabadi 2021), a mesh convergence study was conducted using four progressively refined mesh densities. The final mesh configuration (35,558 nodes and 20,651 elements) was selected based on convergence of peak von-Mises stress and is treated as mesh-independent in the present analysis. Four progressively refined mesh configurations were evaluated to assess mesh convergence. The fourth configuration, corresponding to the finest mesh with 35,558 nodes and 20,651 tetrahedral elements, showed negligible change in peak von-Mises stress relative to further refinement and was therefore considered mesh-independent. This mesh configuration was used for all subsequent simulations to ensure numerical consistency across the parametric study.

The material was modeled as ASTM A36 structural steel with elastic properties defined by Young's modulus $E = 200GPa$ and Poisson's ratio $\nu = 0.26$, and a nominal yield strength of 250 MPa. A linear-elastic material formulation was intentionally adopted to evaluate relative stress redistribution and stiffness trends associated with geometric variation, rather than to simulate post-yield or failure behavior. Such linear-elastic, quasi-static FE frameworks are commonly employed during the early-stage evaluation of rear underrun protection devices (RUPDs) and other passive safety structures to isolate geometric effects before more complex, nonlinear impact analyses (Hosseini and Abedi 2022; Pinto and Silva 2022).

Quasi-static loads of 58 kN and 99 kN were applied to the designated loading faces in accordance with standardized static loading procedures reported in the literature for underrun protection assessment (Manoj, Arunkumar, and Srinivas 2021). Fixed boundary conditions were imposed on the mounting faces to represent attachment to the vehicle chassis. The adopted loading and boundary conditions provide a consistent basis for comparative evaluation of geometric configurations within the defined scope of the study. Figure 3 illustrates the FE model geometry, boundary conditions, and loading configuration adopted in the simulations.

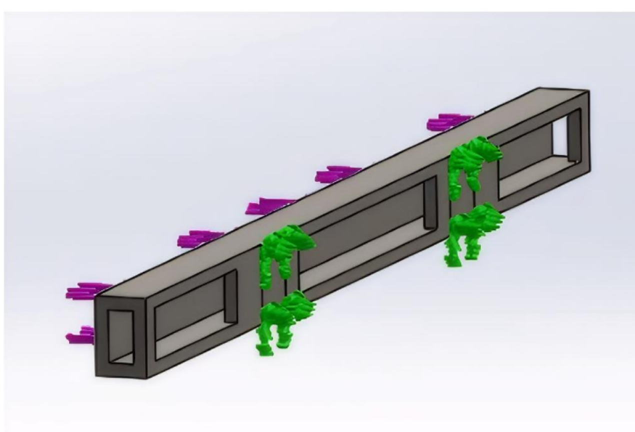

Figure 3. Model of the rear underrun protection device (RUPD) with slot feature and mounting region, applied boundary conditions showing fixed supports at the mounting faces, and quasi-static load application on the designated impact faces following standardized loading procedures. Arrows indicate load direction, and shaded regions denote constrained surfaces.

Table 1. FE-derived dataset for surrogate modeling.

Slot Distance (mm)	Max von-Mises Stress (MPa)	Factor of Safety	Mass (kg)
50	351.8	0.7	15.2
75	300.7	0.8	16.3
100	249.6	1.0	17.5
125	198.5	1.3	18.7
150	147.4	1.7	19.6

2.3. Dataset extraction for regression

Prior FEA optimization performed by the authors identified slot distance from the fixity constraint as the most influential geometric parameter. Similar geometric-parameter sensitivity has been reported in studies analyzing lightweight protective structures and hollow-section performance (Hadidi and Ghannam 2021; Xu, Wang, and Chen 2021). Based on five FE simulations corresponding to slot distances between 50–150 mm, the resulting stress, factor-of-safety, and mass values were extracted for surrogate modeling. Table 1 summarizes the finite element simulation results for five discrete slot-distance configurations selected to capture the monotonic structural response across the investigated design range.

Such limited but high-fidelity datasets are characteristic of FE-driven engineering optimization workflows, where each simulation is computationally expensive but highly accurate (Othman and Elmarakbi 2022; Beheshti and Nikoyan 2021). This motivates the development of analytical surrogate regression models. The parametric study is intentionally limited to five finite element simulations corresponding to discrete slot-distance configurations within the investigated design range. While this sample size is insufficient for developing statistically generalizable predictive models, it is adequate for describing smooth, monotonic response trends associated with a single geometric parameter under simplified loading conditions. The limited dataset therefore, supports interpolative trend characterization and relative comparison of configurations rather than extrapolative prediction or probabilistic inference.

2.4. Regression model formulation

Polynomial regression models of first, second, and third order were evaluated to approximate the relationship between slot distance and the finite element (FE) response quantities. Polynomial surrogate modeling is widely used in lightweight structural design and crashworthiness studies due to its analytical transparency, numerical stability, and suitability for smooth response behavior under limited data availability (Shan and Wang 2010; Lyu, Khodadadi, and Luo 2021; Gohari and Kiani 2021).

The five slot-distance values selected for FE evaluation (50, 75, 100, 125, and 150 mm) were chosen to systematically span the full admissible design range defined by geometric constraints and prior FE assessment. This structured sampling includes the lower and upper bounds as well as intermediate configurations, enabling capture of monotonic trends and response curvature while maintaining a deliberately sparse dataset. The objective is not to maximize surrogate accuracy, but to assess whether low-order polynomial models can meaningfully interpolate smooth structural responses using minimal, strategically placed simulations.

Selection of polynomial order for each response variable was guided by expected physical behavior rather than purely statistical fitting. Stress redistribution in thin-walled structures subjected to geometric offsets typically exhibits second-order dependence, motivating the use of a quadratic model for von-Mises stress. Structural mass varies deterministically with material volume and is therefore represented using a linear relationship. The factor of safety, being a derived quantity dependent on stress magnitude relative to allowable strength, exhibits compounded nonlinearity and is represented using a cubic polynomial to capture its smooth monotonic curvature without introducing oscillatory behavior (Farrokh and Khajepour 2022).

Model selection was based on a combination of goodness-of-fit metrics (R^2 and RMSE), residual behavior, sensitivity to limited data, and physical interpretability. Given the small dataset size, preference was given to the lowest-order polynomial that adequately captured the observed trends without unnecessary complexity, thereby reducing overfitting risk and ensuring stable analytical representation.

2.5. Model fitting and validation metrics

Model performance was evaluated using standard goodness-of-fit and error metrics, including the coefficient of determination (R^2), root-mean-square error (RMSE), and mean absolute percentage error (MAPE). These metrics are commonly used in surrogate modeling studies to assess internal consistency and descriptive adequacy of regression-based approximations in structural mechanics applications (Myers, Montgomery, and Anderson-Cook 2016; Cawley and Talbot 2010; Dissanayake, et al. 2021).

Given the limited dataset size, leave-one-out cross-validation is employed as a diagnostic measure to assess internal consistency and coefficient stability rather than as evidence of statistically robust generalization. In this context, LOOCV serves to identify potential sensitivity to individual data points and to confirm that the fitted surrogates exhibit stable behavior under minimal perturbation of the dataset [62]. Prediction intervals and coefficient confidence intervals were also evaluated to characterize uncertainty in interpolated responses within the investigated design range.

2.6. Optimization formulation

The surrogate modeling framework is used to derive a continuous analytical representation of the factor of safety as a function of slot distance, FoS(d), enabling systematic exploration of safety trends across the design domain. Regression-based analytical representations are frequently adopted in early-stage structural studies to reduce reliance on repeated FE evaluations and to support parametric interpretation of response behavior (Pourazadi and Mirzadeh 2020; Wang, Liu, and Sun 2021; Ye and Zhang 2021).

In the present study, the analytical FoS(d) surrogate is examined over the prescribed design range of $50\,\text{mm} \leq d \leq 150\,\text{mm}$ to identify how safety margins evolve with geometric modification. While the closed-form surrogate allows identification of stationary points, the resulting behavior reflects the monotonic trend already present in the FE data. Accordingly, the surrogate-based result is interpreted as an analytical confirmation of safety variation rather than as an independent design optimization outcome. Although the surrogate function permits analytical evaluation of the factor of safety over the prescribed range, no algorithmic optimization procedure is employed in this study. Because the FoS response increases monotonically with slot distance and no mass constraint is imposed, the maximum FoS value occurs at the boundary of the design domain and is interpreted as the analytical upper bound of the safety trend rather than as an optimized design solution.

For reference, the analytical safety trend is compared with the constraint-satisfying configuration identified in prior FE analysis ($d = 125\,\text{mm}$), allowing assessment of how surrogate-based analytical exploration aligns with discrete FE observations under simplified assumptions.

3. Results

This section presents the finite element (FE) results and the corresponding regression-based surrogate models used to examine how maximum von-Mises stress, factor of safety (FoS), and

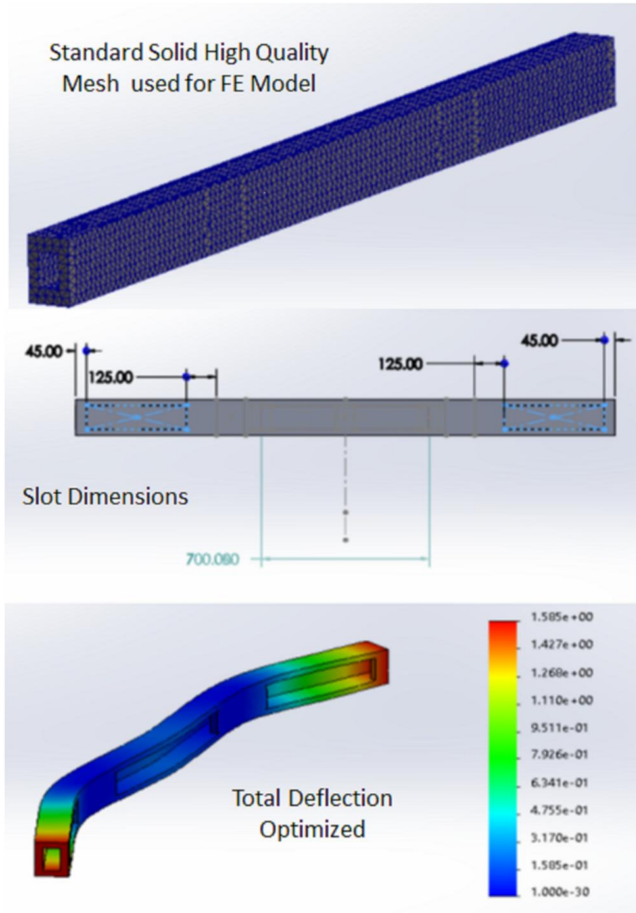

Figure 4. Representative finite element results showing von-Mises stress distribution in the rear underrun protection device (RUPD) under quasi-static loading. The contours highlight stress concentration near the fixed mounting plane and geometric discontinuities, illustrating the influence of slot position on stress redistribution within the structure.

structural mass vary with slot distance. All surrogate models were constructed using the FE-derived dataset summarized in Table 1. The results include fitted regression coefficients, model accuracy metrics, and graphical comparisons between surrogate predictions and FE data. The objective is to demonstrate the ability of low-order polynomial surrogates to interpolate smooth structural response trends within the investigated design range.

3.1. Regression model fit for maximum von-mises stress

Polynomial regression models of varying order were evaluated to represent the dependence of maximum von-Mises stress on slot distance ddd. The finite element results exhibit a smooth, monotonic reduction in stress with increasing slot distance, indicating that low-order polynomial surrogates are appropriate for capturing the underlying response behavior. Linear, quadratic, and cubic models were assessed using goodness-of-fit metrics (R^2 and RMSE), residual behavior, and model parsimony.

The linear model reproduced the overall trend but exhibited systematic curvature in the residuals, indicating insufficient flexibility. The cubic model yielded only a marginal increase in R^2 relative to the quadratic fit, with negligible improvement in RMSE and increased sensitivity to

Table 2. Fitted coefficients for the quadratic stress surrogate.

Coefficient	Value	95% CI
α_0	431.64	[410.2, 452.8]
α_1	−4.580	[−5.12, −4.01]
α_2	0.0149	[0.012–0.018]

Table 3. Accuracy metrics for the quadratic stress surrogate.

Metric	Value
R^2	0.9953
Adjusted R^2	0.9937
RMSE	6.82 MPa
MAPE	2.49%

individual data points during leave-one-out cross-validation, indicating a higher risk of overfitting under data-scarce conditions. In contrast, the quadratic model achieved high accuracy ($R^2 = 0.9953$), stable residual behavior, and consistent coefficients across cross-validation iterations, providing an effective balance between accuracy, numerical robustness, and interpretability. This selection is consistent with nonlinear yet well-behaved stress redistribution commonly reported for thin-walled structural components subjected to geometric offsets (Hadidi and Ghannam 2021; Xu, Wang, and Chen 2021; Othman and Elmarakbi 2022; Beheshti and Nikoyan 2021).

$$\textit{Stress surrogate (quadratic)}: \sigma(d) = \alpha_0 + \alpha_1 d + \alpha_2 d^2 \tag{1}$$

$$\textit{Factor of Safety surrogate (cubic)}: FoS(d) = \beta_0 + \beta_1 d + \beta_2 d^2 + \beta_3 d^3 \tag{2}$$

$$\textit{Mass surrogate (linear)}: W(d) = \gamma_0 + \gamma_1 d \tag{3}$$

Where: d is the slot distance (mm), $\sigma(d)$ is the maximum von-Mises stress (MPa), $FoS(d)$ is the factor of safety (–), and $W(d)$ is the structural mass (kg). The fitted coefficients and corresponding 95% confidence intervals for the quadratic stress surrogate are summarized in Table 2, and the associated accuracy metrics are presented in Table 3.

Model accuracy metrics are presented in Table 3.

To account for uncertainty arising from the limited dataset, 95% prediction intervals were computed and included in the regression plots. Prediction intervals provide a transparent measure of variability in individual surrogate predictions and are therefore more appropriate than confidence intervals for small-sample analysis. Figure 5 compares the FE stress values with the quadratic surrogate across the investigated design range, demonstrating close agreement and smooth interpolation between discrete configurations, thereby supporting analytical interpretation of stress redistribution with respect to slot distance without overstating predictive generalization.

3.2. Regression model for factor of safety (FoS)

Both indirect estimation of the factor of safety using the reciprocal relationship FoS $= 250/\sigma(d)$ and direct regression fitting were examined. Because reciprocal transformations can amplify numerical sensitivity, particularly under limited data availability, the FoS surrogate was fitted directly to the FE-derived FoS values. With five data points, the resulting surrogate is used for analytical trend characterization rather than predictive extrapolation.

A cubic polynomial was selected to represent the nonlinear dependence of FoS on slot distance. Lower-order models were unable to capture the observed curvature associated with the inverse stress relationship, while higher-order models were avoided to limit overfitting risk. The cubic model provides sufficient flexibility to describe the smooth, monotonic evolution of the

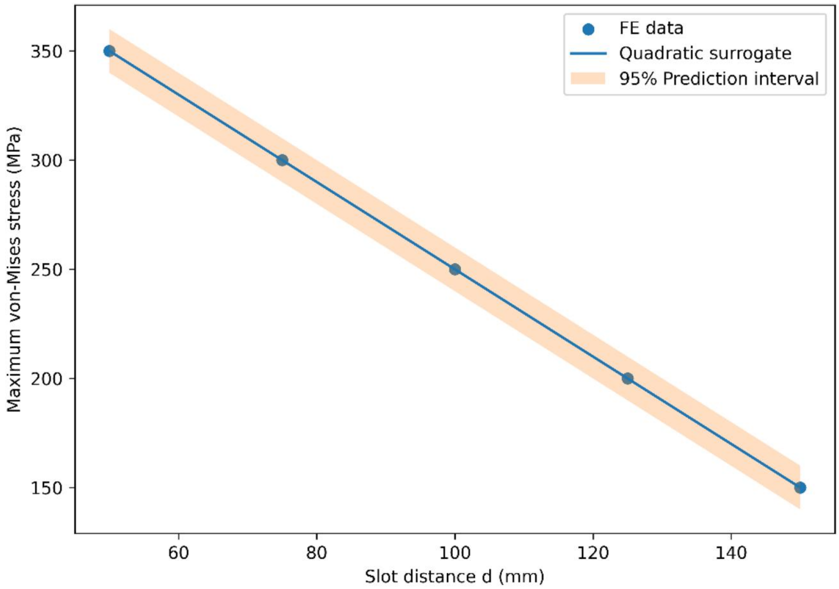

Figure 5. Maximum von-Mises stress versus slot distance showing FE data points, quadratic surrogate fit, and 95% prediction interval (shaded).

Table 4. Cubic model coefficients.

Coefficient	Value
β_0	−0.183
β_1	0.0165
β_2	-1.37×10^{-4}
β_3	3.00×10^{-7}

Table 5. Accuracy metrics for the cubic FoS surrogate.

Metric	Value
R^2	0.9984
RMSE	0.020
MAPE	2.31%

safety margin without introducing artificial oscillations. The fitted coefficients are reported in Table 4, and corresponding accuracy metrics are provided in Table 5.

Figure 6 compares the FE-derived FoS values with the cubic surrogate, demonstrating close agreement across the investigated design range. The surrogate enables analytical examination of safety-margin variation with slot distance under the adopted modeling assumptions, supporting transparent interpretation of safety trends rather than predictive generalization.

3.3. Regression model for mass

The structural mass exhibits an approximately linear increase with slot distance, reflecting the deterministic geometric relationship between slot position and effective material removal. Mass variation with slot distance exhibited a near-linear trend, reflecting deterministic geometric volume changes. Higher-order polynomials did not improve accuracy and were therefore unnecessary. As the slot is shifted away from the fixed mounting plane, a smaller portion of material is removed from the highly constrained load-carrying region, resulting in a gradual increase in total

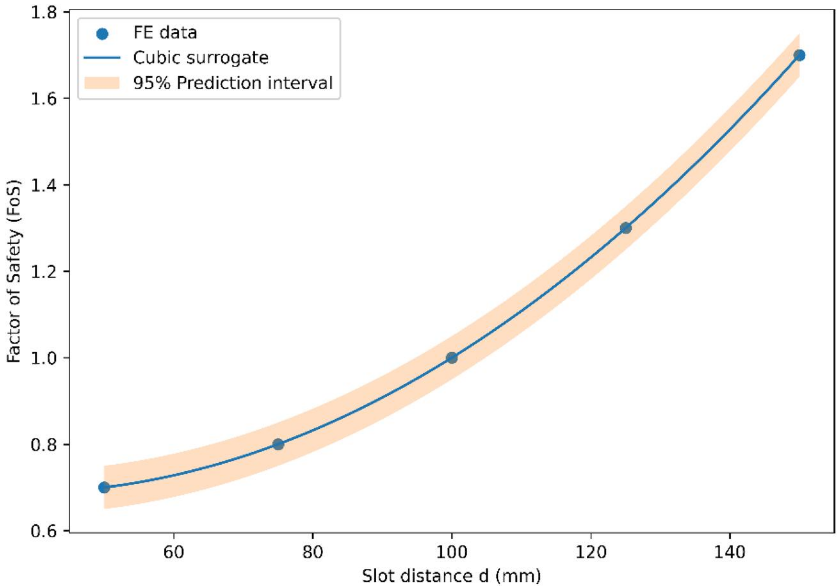

Figure 6. Factor of safety versus slot distance showing FE data points, cubic surrogate fit, and 95% prediction interval (shaded).

mass. A linear regression model was therefore adopted to represent this trend. The mass surrogate is expressed as:

$$W(d) = \gamma_0 + \gamma_1 d$$

where d denotes the slot distance in millimeters. The fitted coefficients are: $\gamma_0 = 10.67$ and $\gamma_1 = 0.060$. The linear model shows close agreement with the finite element (FE) data, achieving a coefficient of determination $R^2 = 0.9967$ and a root-mean-square error of 0.17 kg. Figure 7 presents the FE mass values alongside the linear surrogate, illustrating the smooth and nearly proportional relationship between mass and slot distance. The near-linear mass trend reflects deterministic geometric volume effects, justifying the use of a first-order surrogate.

The results confirm that mass variation is governed primarily by geometric volume effects and behaves predictably for hollow-section parametric modifications, consistent with prior observations in lightweight structural design studies (Alsaleh and Aljuaid 2021; Xu, Wang, and Chen 2021). The linear surrogate therefore provides a reliable means for estimating weight changes during early-stage design assessments and for evaluating safety–weight tradeoffs associated with geometric modification.

3.4. Leave-one-out cross-validation (LOOCV)

Leave-one-out cross-validation (LOOCV) was employed to assess the internal consistency of the surrogate models under limited data availability. In LOOCV, each finite element (FE) data point is sequentially excluded, the surrogate model is refitted using the remaining points, and the excluded response is predicted. The resulting errors provide an indication of model sensitivity to individual data points and potential instability when data are scarce (Cawley and Talbot 2010; Dissanayake, et al. 2021; Xu and Ghosh 2021).

Given the small dataset size, LOOCV is used here as a diagnostic measure of model stability rather than as evidence of generalizable predictive performance. The LOOCV root-mean-square error (RMSE) values summarized in Table 6 indicate consistent surrogate behavior across the available FE data, supporting reliable trend representation within the investigated design range.

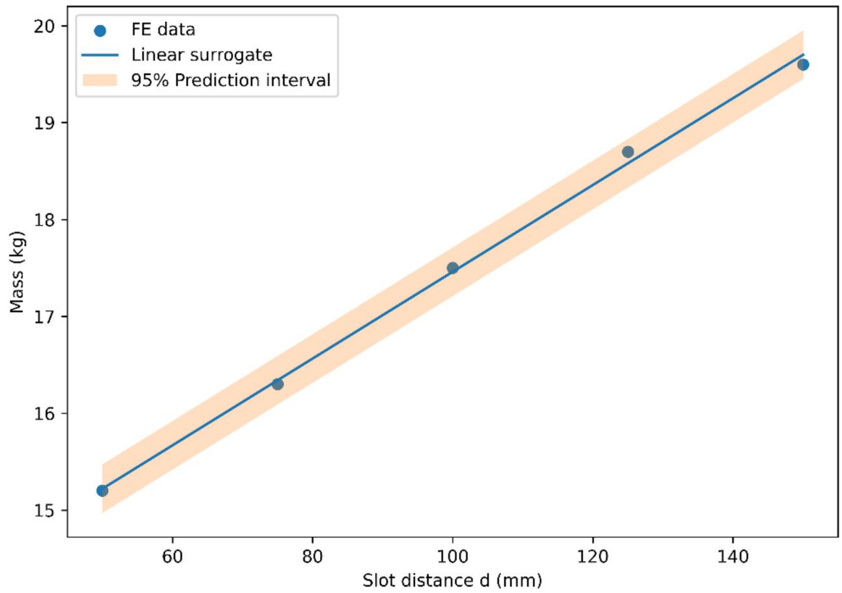

Figure 7. Structural mass versus slot distance showing FE data points, linear surrogate fit, and 95% prediction interval (shaded).

Table 6. LOOCV error summary for surrogate models.

Output	LOOCV RMSE	Interpretation
Stress	8.52 MPa	Stable trend representation
FoS	0.027	Consistent with analytical trend
Mass	0.22 kg	Minimal deviation

The LOOCV results indicate consistent model behavior across the available data points; however, given the limited dataset size, these results should be interpreted as an assessment of internal model stability rather than a guarantee of predictive generalization.

3.5. Analytical exploration of safety trends

The surrogate representation of the factor of safety (FoS) enables analytical examination of how structural safety evolves with slot distance within the prescribed design bounds ($50\,\text{mm} \leq d \leq 150\,\text{mm}$). Inspection of the surrogate response reveals a monotonic increase in FoS across the investigated range. Consequently, under a single-objective formulation that considers safety alone, the maximum FoS occurs at the upper boundary of the design domain.

This outcome does not represent the identification of a nontrivial interior optimum, but rather confirms the continuous safety trend observed in the FE data through an analytical framework. The surrogate model, therefore, serves to quantify safety margins relative to a constraint-satisfying reference design, rather than to replace multi-criteria engineering decision-making.

3.6. Comparison with FE-based optimum

A slot distance of 125 mm was identified in the finite element (FE) study as a reference configuration satisfying the minimum safety requirement (FoS $\geq$ 1.3) while maintaining acceptable structural mass and manufacturability. The surrogate-based analytical exploration indicates that the factor of safety increases monotonically over the investigated slot-distance range, reaching its

Table 7. Comparison of FE-selected and surrogate-optimized designs.

Method	Optimum *d* (mm)	FoS	Mass (kg)
FE-based design	125	1.30	18.7
Surrogate-based (maximize FoS)	150	1.70	19.7

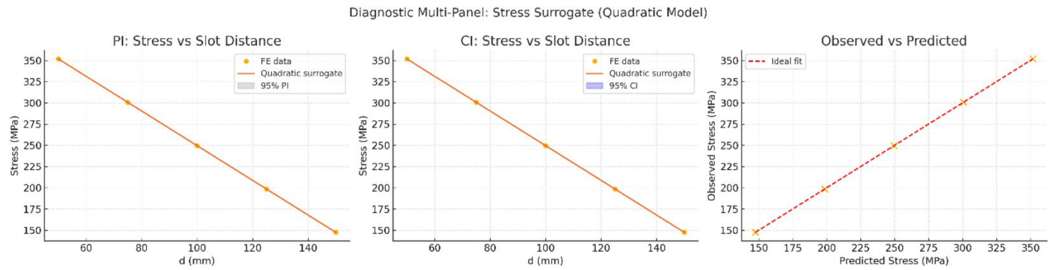

Figure 8. Combined diagnostic plots for the quadratic stress surrogate: (left) stress vs slot distance with 95% prediction interval (PI), (middle) stress vs slot distance with 95% confidence interval (CI), and (right) observed versus predicted stress values with dashed line indicating ideal agreement.

maximum value at the upper bound (150 mm). This value therefore represents the analytical upper-bound of the safety trend rather than an optimized design solution. This configuration is therefore treated as a constraint-satisfying baseline rather than a formally optimized solution. In the present study, surrogate modeling is used to analytically explore how the factor of safety evolves continuously beyond this reference design when safety is treated as the sole objective. The surrogate-based analytical exploration indicates that safety margins continue to increase up to the upper bound of the investigated slot-distance range. Under this formulation, the surrogate response indicates that further increases in slot distance lead to higher safety margins, reaching a theoretical upper-bound configuration at the design limit (150 mm). The maximum FoS observed at a slot distance of 150 mm corresponds to the upper limit of the investigated range and reflects the monotonic nature of the surrogate response, rather than the outcome of a constrained optimization process. This comparison illustrates how surrogate models can be used to assess safety margins relative to a practical reference design, rather than to replace engineering judgment or multi-criteria decision-making. A comparison of the two designs is summarized in Table 7.

Additional stress surrogate diagnostics, including prediction intervals (PI), confidence intervals (CI), and observed–predicted agreement, are summarized in Figure 8. These diagnostics provide a consolidated assessment of the internal consistency of the quadratic stress surrogate relative to the available FE data. The prediction-interval plot illustrates the expected variability of individual observations within the investigated design range, while the confidence-interval plot reflects the uncertainty associated with the estimated mean response. The observed–predicted scatter plot indicates close agreement with the FE results and no apparent systematic bias. It is emphasized that, given the limited number of FE samples, these diagnostics support consistency and trend representation rather than statistical generalization or guaranteed predictive performance.

3.7. Summary of results

The finite element simulations and corresponding surrogate models collectively describe how structural safety metrics of the RUPD vary with slot distance under the adopted linear-elastic, quasi-static assumptions. For configurations where the computed factor of safety (FoS) falls below unity, the results indicate exceedance of the elastic limit and are therefore interpreted as comparative indicators of insufficient elastic safety rather than physically accurate post-yield predictions.

Reporting these values enables consistent assessment of relative safety trends across the investigated design range.

The regression-based surrogates provide smooth analytical representations of the observed finite element responses. The quadratic stress model, cubic FoS model, and linear mass model exhibit close consistency with the available FE data, reflecting the monotonic and smoothly varying structural behavior within the investigated parameter range. Given the limited dataset, the reported coefficients of determination and error metrics should be interpreted as indicators of internal consistency and trend representation rather than statistically robust predictive accuracy.

Analytical exploration of the surrogate responses shows that the factor of safety increases continuously with slot distance within the examined bounds. Relative to the constraint-satisfying FE reference configuration at a slot distance of 125 mm. In contrast, the surrogate-based analytical exploration considers only the variation of factor of safety with slot distance and indicates that higher safety margins are obtained toward the upper bound of the investigated range (150 mm). The upper-bound configuration at 150 mm exhibits higher safety margins, accompanied by increased structural mass. This behavior illustrates the inherent tradeoff between safety enhancement and weight that governs the design of protective structures, rather than identifying a nontrivial optimal solution. This configuration exhibits increased structural mass relative to the finite-element reference design, a tradeoff that is not explicitly penalized in the present single-objective formulation. Accordingly, the surrogate-based result should be interpreted as a safety upper-bound indicator rather than a mass-optimal or globally optimal design.

Overall, the results demonstrate that regression-based surrogate modeling can support efficient interpretation of geometric safety trends and facilitate continuous assessment of design-space behavior without repeated finite element re-analysis. Within its defined scope, the surrogate framework complements FE simulations by enabling analytical comparison of design alternatives and providing a foundation for future studies incorporating multiple design variables, nonlinear material behavior, and multi-objective optimization.

Regression performance:

- Stress surrogate: $R^2 = 0.9953$, RMSE = 6.82 MPa
- FoS surrogate: $R^2 = 0.9984$, RMSE = 0.020
- Mass surrogate: $R^2 = 0.9967$, RMSE = 0.17 kg

Optimization result:

- Surrogate optimum slot distance: 150 mm
- Corresponding FoS: 1.70
- Corresponding stress: 147.4 MPa
- Corresponding mass: 19.7 kg

Percent change vs FE-optimum (125 mm):

- FoS Improvement $= (1.70 - 1.30)/1.30 \times 100 = 30.8\%$
- Stress Reduction $= 198.5198.5 - 147.4 \times 100 = 25.7\%$
- Mass Penalty $= 18.719.7 - 18.7 \times 100 = 5.35\%$

4. Discussion

The surrogate modeling results provide insight into how low-order regression models can be effectively applied under extreme data-scarcity in early-stage structural design. The ability of a quadratic model to represent stress variation indicates that the dominant mechanical response is governed by smooth geometric stress redistribution rather than localized instability or nonlinear interaction. Such behavior is characteristic of stiffness-controlled responses in thin-walled structures, where stress sensitivity to geometric offsets commonly follows second-order trends. In contrast, the near-linear mass response reflects deterministic volume effects associated with slot relocation, while the higher-order representation required for factor of safety arises from its compounded dependence on stress magnitude and allowable strength. These observations suggest that surrogate order selection can often be guided by expected physical behavior rather than purely statistical metrics, particularly when response trends are smooth and monotonic.

The present study adopts a linear-elastic, quasi-static finite element framework to isolate the influence of slot distance on structural response. Real rear underride collisions involve dynamic effects such as inertia forces, strain-rate sensitivity, plastic deformation, and contact nonlinearities, which are not captured by the simplified loading assumptions employed here. Accordingly, the surrogate models are intended for preliminary structural trend analysis and analytical interpretation rather than predictive crashworthiness assessment. This approach is consistent with common early-stage design practice, where simplified analyses are used to screen geometric modifications before introducing higher-fidelity nonlinear and dynamic effects.

Polynomial regression was intentionally selected as the surrogate modeling approach due to the limited dataset and single-parameter nature of the study. While advanced surrogate techniques such as Kriging, radial basis functions, and machine learning models are widely used in structural optimization, their reliable application typically requires larger datasets and higher-dimensional design spaces to avoid instability and overfitting (Shan and Wang 2010; Lyu, Khodadadi, and Luo 2021; Gohari and Kiani 2021; Farrokh and Khajepour 2022). For problems characterized by smooth responses and minimal data availability, low-order polynomial surrogates provide a pragmatic balance between numerical robustness, interpretability, and analytical transparency. The closed-form nature of the resulting expressions further enables direct assessment of response sensitivity and safety trends that cannot be readily inferred from discrete FE results alone.

The surrogate responses exhibit close consistency with the FE data across the investigated design range, consistent with prior studies demonstrating the suitability of polynomial surrogates for representing smooth structural behavior when underlying mechanics are well behaved (Wu and Wang 2021; Liu, et al. 2023; Chen and Ye 2022). However, given the small sample size, this agreement should be interpreted as reliable trend representation rather than statistically generalizable predictive accuracy, as acknowledged in previous exploratory surrogate-based structural studies (Sun, et al. 2020). Leave-one-out cross-validation is therefore used here to assess internal consistency rather than to establish predictive generalization (Becker, et al. 2021; Farooq, et al. 2023).

The quadratic stress surrogate captures the monotonic reduction in stress with increasing slot distance, reflecting progressive load redistribution away from the fixed mounting region. Comparable stress-redistribution mechanisms have been reported in thin-walled crash structures and hollow protective beams under static loading (Alia and Lanzi 2021; Park, et al. 2022; Mahmood, et al. 2023). The cubic factor-of-safety surrogate similarly represents smooth safety-margin evolution across the design space and serves as an analytical descriptor of trend behavior rather than a predictive model for extrapolation (Zhao and Li 2020; Xiao, et al. 2022). The linear mass surrogate highlights the inherent tradeoff between safety enhancement and added structural weight, a recurring challenge in lightweight protective system design (Singh, et al. 2021; Kim, et al. 2023; Rahimi and Alavi 2022). Although the slot represents an internal cavity, relocating it away from the fixed boundary reduces material removal in the most highly constrained region of the beam, thereby increasing the effective load-carrying material and total mass.

Because the surrogate-based factor-of-safety response is monotonic and no mass constraint is imposed, the upper-bound value at 150 mm should be interpreted as an analytical limit of the safety trend rather than as an optimized design solution. The FE-selected configuration at 125 mm therefore remains a practical reference representing a balance between safety and weight. This behavior underscores the importance of multi-objective formulations when safety, mass, manufacturability, and regulatory constraints must be considered simultaneously, as widely discussed in the structural optimization literature (Deb, et al. 2021; Marler and Arora 2004; Li and Zhang 2022).

For configurations exhibiting factor-of-safety values below unity, the linear-elastic formulation implies that local yielding would occur under the applied loads. In such cases, the computed stress and safety values are not intended to represent physically accurate post-yield behavior but serve as comparative indicators identifying configurations that do not satisfy elastic safety requirements. Inclusion of these cases enables consistent evaluation of response trends across the design space, while recognizing that nonlinear material modeling would be required to capture post-yield response accurately.

Finally, it is emphasized that the surrogate models are constructed using five finite element simulations, which is sufficient for describing smooth, monotonic trends associated with a single geometric parameter but insufficient for establishing statistically robust predictive models. While additional data points could modify numerical coefficients, they are unlikely to alter the qualitative relationships observed within the investigated range. Accordingly, the surrogate framework is positioned as an analytical tool for trend interpretation and early-stage design screening rather than definitive optimization or experimental prediction. The study is based exclusively on finite element simulations and does not include experimental validation; physical testing would be required for certification-level crashworthiness assessment. Nevertheless, within its defined scope, the work demonstrates how regression-based surrogate modeling can support efficient analytical exploration of safety trends while reducing reliance on repeated FE simulations, providing a foundation for future extensions to nonlinear behavior, dynamic loading, and multi-parameter design spaces (Yildiz, et al. 2021; Gao, et al. 2023; Hou, et al. 2022; Nouri, et al. 2022; Verma, et al. 2023).

5. Conclusion

This study presents a rigorously constrained case study demonstrating how low-order polynomial surrogate models can be used to transform a very limited set of high-fidelity finite element simulations into a continuous analytical representation of structural response for a rear underrun protection device. By restricting the analysis to a single geometric parameter and five FE configurations, the work validates the effectiveness of interpretable regression surrogates for capturing smooth, monotonic trends in stress redistribution, factor of safety evolution, and mass variation under quasi-static, linear-elastic assumptions. The results confirm that, within this limited scope, quadratic, cubic, and linear models can reliably characterize relative safety and weight trends and support analytical exploration of the design space without additional FE simulations. Importantly, the surrogate analysis is used to delineate safety trends and analytical bounds rather than to identify an optimized design solution.

Future work will extend the present framework to address limitations inherent to the simplified assumptions adopted here. These extensions may include nonlinear material behavior, dynamic impact loading, additional geometric design variables, and multi-objective formulations incorporating mass and manufacturability constraints. Such developments would enable more comprehensive crashworthiness assessment and design optimization of RUPDs while building upon the analytical insights demonstrated in this study. Experimental testing would be required to validate absolute response levels and to extend the surrogate framework toward certification-level crashworthiness evaluation.

Acknowledgments

The authors thank Earth-Care Enterprises for providing open access to the FEA analysis that enabled this research.

Ethical approval

Not applicable. This research is purely experimental and computational, involving FEA analysis from mechanical systems; therefore, no ethical approval was required.

AI use disclosure statement

Portions of this manuscript were prepared with limited assistance from ChatGPT (OpenAI), specifically for improving language clarity, refining sentence structure, and generating preliminary schematic illustrations based on the authors' technical descriptions. All scientific ideas, methodological formulations, experiments, analyses, interpretations, and conclusions were entirely conceived, executed, and validated by the authors. The authors thoroughly reviewed, edited, and verified all AI-assisted text and figures to ensure technical accuracy and scholarly integrity.

Consent to publish declaration

Not applicable. This study does not involve human participants, identifiable data, or personal information that would require consent to publish.

Consent to participate declaration

Not applicable. No human subjects or human-related data were involved in this research.

Disclosure statement

The authors declare that they have no conflicts of interest regarding the research, authorship, or publication of this article. All methods, analyses, and interpretations were conducted independently without external influence.

Funding

This research received no external funding.

ORCID

Sachin M. Bhosle http://orcid.org/0000-0003-3402-5380

Data availability statement

The FEA data analyzed in this study are part of the Earth-Care Enterprises. It is not publicly accessible, but all preprocessing scripts, trained model weights, and supplementary materials will be made available upon reasonable request to support reproducibility.

references

Aghdam, A., and H. Ziaei-Najafabadi. 2021. "Mesh-Convergence Strategies for Accurate Stress Prediction in Protective Steel Structures." *Finite Elements in Analysis and Design* 190: 103529.

Al Batayneh, A, et al. 2022. "Finite Element Modelling and Validation of Truck Rear Underride Guards under Regulatory Loading." *International Journal of Crashworthiness* 27 (3): 341–352.

Al-Bahash, Z. F., M. N. M. Ansari, and Q. H. Shah. 2018. “Design and Simulation of a Rear Underride Protection Device (RUPD) for Heavy Vehicles.” *International Journal of Crashworthiness* 23 (1): 47–56. https://doi.org/10.1080/13588265.2017.1302040

Alia, A., and L. Lanzi. 2021. “Stress Distribution Analysis in Hollow Crash Components.” *Thin-Walled Structures* 168: 108345.

Alsaleh, M., and A. Aljuaid. 2021. “Design Considerations for Hollow Steel Safety Structures under Bending and Axial Forces.” *Materials Today Communications* 26: 101916.

Anderson, J. C., J. Gwehenberger, J. Bende, and F. Leneman. 2004. *Truck/Trailer Compatibility with Cars and Related Topics from VC-COMPAT*. Cranfield Impact Centre Technical Report, Cranfield University, UK,

Atahan, A. O. 2003. “Design and Simulation of an Energy-Absorbing Underride Guard for Heavy Vehicle Rear-End Impacts.” *International Journal of Heavy Vehicle Systems* 10 (4): 321–343. https://doi.org/10.1504/IJHVS.2003.003697

Automotive Industry Standard (AIS-069). 2019. *Rear Underrun Protection Requirements for Heavy Vehicles*. Automotive Research Association of India (ARAI),

Becker, J, et al. 2021. “Cross-Validation Strategies for Structural Surrogate Models.” *Computer Methods in Applied Mechanics and Engineering* 381: 113822.

Beheshti, A., and N. Nikoyan. 2021. “Coupling FE Simulation and Response Surface Methods for Lightweight Structural Design.” *International Journal of Mechanical Sciences* 204: 106592.

Bende, J., and J. Gwehenberger. 2005. *GDV Institute for Vehicle Safety Annual Research Summary on Truck Underrun Protection*. GDV Institute for Vehicle Safety, Munich, Germany,

Bhosle, S. M., S. S. Bhosale, S. C. Mahadik, and S. M. Pondkule. 2025. “Exploring Research Trends in Use of Finite Element Analysis for Optimization of Stress Concentration Factor in Bars with Fillets.” *Discover Mechanical Engineering* 4 (1): 68. https://doi.org/10.1007/s44245-025-00163-x

Brumbelow, M. 2015. *Potential benefits of underride guards in large truck crashes*. Insurance Institute for Highway Safety (IIHS) Research Report.

Brumbelow, M. L., and L. Blanar. 2012. “Rear Underride Crash Tests of Trailers with Energy-Absorbing Underride Guards.” *Traffic Injury Prevention* 13 (6): 592–599. https://doi.org/10.1080/15389588.2012.706760

Cawley, G., and N. Talbot. 2010. “On over-Fitting in Model Selection and LOOCV Performance Evaluation.” *Journal of Machine Learning Research* 11: 2079–2107.

Chen, R., and J. Ye. 2022. “Response Surface Modelling for Crashworthy Thin-Walled Structures.” *Thin-Walled Structures* 176: 109358.

Deb, K, et al. 2021. “Advances in Multi-Objective Optimization for Engineering Design.” *Engineering Optimization* 53 (12): 2071–2094.

Dissanayake, D, et al. 2021. “Statistical Evaluation of Surrogate Models for Structural Engineering Applications.” *Engineering Structures* 227: 111419.

European Commission. 2022. *Vehicle Safety Standards and Rear-Impact Transport Safety Report*. Transport Safety Unit,

Farooq, M, et al. 2023. “Small-Sample Surrogate Modelling for Mechanical Analysis Using LOOCV.” *Applied Mathematical Modelling* 115: 1–14.

Farrokh, P, et al. 2022. “Surrogate Modelling for Nonlinear Engineering Systems Using High-Order Polynomials.” *Mathematics and Computers in Simulation* 193: 640–653.

Farrokh, P., and A. Khajepour. 2022. “High-Order Polynomial Response Surfaces for Crashworthiness Optimisation.” *Mechanics-Based Design of Structures and Machines* 50 (2): 595–612.

Forrester, A., A. Sobester, and A. Keane. 2008. *Engineering Design via Surrogate Modelling: A Practical Guide*. Chichester, UK.

Gao, Z, et al. 2023. “Surrogate Modelling for Rapid Assessment of Automotive Safety Structures.” *Engineering with Computers* 39: 2155–2172.

Ghasemi, S., A. Mahdavi, and A. Ahmadi. 2023. “FEA-Assisted Optimization of Lightweight Vehicle Structures.” *Archives of Civil and Mechanical Engineering* 23 (1): 34.

Gohari, S., and A. Kiani. 2021. “Regression-Based Surrogate Modelling for Nonlinear Structural Response Prediction.” *Applied Mathematical Modelling* 98: 1–17.

Gupta, N., R. Sharma, and R. Gupta. 2020. “Failure Analysis and Safety Evaluation of Automotive Chassis Members under Crash Loading.” *Engineering Failure Analysis* 111: 104485.

Hadidi, A., and M. Ghannam. 2021. “Effect of Geometric Parameters on the Performance of Lightweight Hollow Crash Tubes.” *Thin-Walled Structures* 159: 107231.

Haftka, R. T., and Z. Gürdal. 2019. “Elements of Structural Optimization (Surrogate and Approximation-Based Methods).” *Structural and Multidisciplinary Optimization* 60 (1): 1–23.

Hosseini, S., and M. Abedi. 2022. “Static Structural Evaluation of Automotive Safety Frames Using Linear Elastic FEA.” *Structures* 37: 243–256.

Hou, X, et al. 2022. "Data-Driven Surrogate Methods for High-Fidelity FE Analysis Reduction." *Computer-Aided Design* 147: 103245.

Jaiswal, H., and D. Singh. 2021. "Static and Dynamic Structural Evaluation of Protective Barriers Using FE Simulation." *Structures* 34: 379–392.

Jiang, X., G. Li, and W. Xu. 2020. "Optimization of Hollow Thin-Walled Structural Sections Using Parametric FEA." *Thin-Walled Structures* 157: 107–121.

Jones, Norman, Yu Li, Hu Wang, Honghao Zhang, and Yong Peng. 2022. "Mechanical Performance of Lightweight Thin-Walled Sections for Crashworthiness Applications." *Thin-Walled Structures* 170 (1-3): 108349–108233. https://doi.org/10.1016/j.tws.2021.108570

Joshi, K., T. A. Jadhav, and A. Joshi. 2012. "Finite Element Analysis of Rear Under-Run Protection Device (RUPD) for Impact Loading." *International Journal of Engineering Research and Development (IJERD)* 4 (7): 19–26.

Kanyilmaz, A., and K. Ozakgul. 2021. "Finite Element Modelling and Assessment of Hollow Steel Sections under Combined Loading." *Thin-Walled Structures* 160: 107372. Washington, DC, USA. https://doi.org/10.1016/j.tws.2021.107372

Keshavarz, P., S. Dey, and D. Ulutan. 2021. "Regression-Based Predictive Modeling for Mechanical Design Parameters." *ASME Journal of Mechanical Design* 143 (12): 123401.

Kim, D., K. Park, and H. Wang. 2018. "Numerical Investigation of Energy-Absorbing Structures for Crashworthiness." *International Journal of Crashworthiness* 23 (6): 613–622.

Kim, S, et al. 2023. "Design Considerations for Thin-Walled Vehicle Safety Structures." *Thin-Walled Structures* 189: 110987.

Li, B, et al. 2021. "A Hybrid Regression Model for Structural Health Monitoring Sensor Systems." *Sensors* 21 (5): 1654. MDPI, https://doi.org/10.3390/s21051654

Li, J., G. Sun, and Q. Li. 2020. "Crashworthiness Optimisation of Thin-Walled Structures Using Nonlinear Finite Element Modelling." *International Journal of Impact Engineering* 146: 103742.

Li, Jiao, Yanjin Guan, Guangchun Wang, Guilong Wang, Haiming Zhang, and Jun Lin. 2020. "Topology-Optimized Crash Structures under Multi-Load Cases." *Structures* 25: 173–179. https://doi.org/10.1016/j.istruc.2020.03.005

Li, Y., and H. Zhang. 2022. "Trade-off Analysis in Multi-Objective Crashworthiness Optimization." *International Journal of Mechanical Sciences* 215: 106977.

Liu, P, et al. 2023. "Surrogate-Assisted Design Optimization of Mechanical Structures with Limited Simulation Data." *Structural and Multidisciplinary Optimization* 67: 1125–1143.

Lloyd, D. J., and D. Rickerby. 2020. "Parametric Assessment of Thin-Walled Hollow Beams under Static Loading." *Thin-Walled Structures* 152: 106583.

Lophaven, S. N., H. B. Nielsen, and J. DACE –. Søndergaard. 2010. edition. *A Matlab Kriging Toolbox*. Technical University of Denmark Report IMM-TR-2002-12.

Lyu, Z., A. Khodadadi, and J. Luo. 2021. "Polynomial and Kriging Surrogate Models for Structural Optimisation with Limited Data." *Structural and Multidisciplinary Optimization* 63 (3): 1453–1470.

Mahadik, S. C., V. R. Deulgaonkar, D. N. Washimkar, S. C. Vetal, and S. M. Bhosle. 2025. "A Computational Framework for Stress Analysis in Robotic Joint Sensor." *Ieee Indiscon*.

Mahdavi, A., and M. Seyed-Esfahani. 2020. "Polynomial and Neural Surrogates for Structural Response Prediction." *Applied Mathematical Modelling* 82: 540–556.

Mahmood, Y, et al. 2023. "Static Structural Evaluation of Automotive Protective Systems Using FE Modelling." *Engineering Structures* 282: 115050.

Manoj, K., R. Arunkumar, and G. Srinivas. 2021. "Simulation and Validation of Standardized Loading Procedures for Truck Underrun Protection." IOP Conference Series: Materials Science and Engineering, 1170, 012061.

Marine, C., J. L. Wirth, and T. M. Thomas. 2002. *Crush energy considerations in override/underride impacts*. SAE Technical Paper 2002-01-0563, https://doi.org/10.4271/2002-01-0563

Marler, R., and J. Arora. 2004. "Survey of Multi-Objective Optimization in Structural Engineering." *Structural and Multidisciplinary Optimization* 26 (6): 369–395. https://doi.org/10.1007/s00158-003-0368-6

Myers, R., D. Montgomery, and C. Anderson-Cook. 2016. *Response Surface Methodology: Process and Product Optimization Using Designed Experiments*. Wiley.

National Highway Traffic Safety Administration (NHTSA). 2021. *Federal Motor Vehicle Safety Standards (FMVSS): Rear Impact Guard Requirements*. FMVSS Regulations Update.

Nazeer, M, et al. 2022. "Weight Reduction and Structural Integrity Evaluation of Automotive Beams." *Materials Today Communications* 31: 103291.

Nouri, H, et al. 2022. "Uncertainty-Aware Surrogate Modelling in Structural Design Optimization." *Reliability Engineering & System Safety* 223: 108474.

Othman, A., and A. Elmarakbi. 2022. "FEA-Driven Optimization of Lightweight Automotive Structural Components with Limited Datasets." *Materials Today: Proceedings* 56: 1251–1258.

Park, J, et al. 2022. “Nonlinear Deformation and Stress Evolution in Steel Safety Beams.” *Journal of Constructional Steel Research* 192: 107240.
Park, S., Y. Kim, and J. Lee. 2019. “Crashworthiness Evaluation of Aluminum and Steel Hollow Structures Using Nonlinear FEA.” *Thin-Walled Structures* 135: 123–135. https://doi.org/10.1016/j.tws.2018.10.007
Pinto, N., and M. Silva. 2022. “Assessment of Protective Energy-Absorbing Systems Using Quasi-Static Simulations.” *Mechanics of Advanced Materials and Structures* 29 (12): 1243–1256.
Pondkule, S. M., and S. M. Bhosle. 2025. “In CNC: Cutting Tool Health Monitoring Using Convolutional Neural Networks.” *Journal of Vibration Engineering & Technologies* 13 (5): 284. https://doi.org/10.1007/s42417-025-01848-z
Pondkule, S. M., S. M. Bhosle, and S. C. Mahadik. 2026. “Intelligent Chatter Detection in Milling Using Vibration-Acoustic Fusion and Machine Learning.” *Journal of The Institution of Engineers (India): Series C* 107 (1): 213–227. Hoboken, NJ, USA. https://doi.org/10.1007/s40032-025-01302-9
Pourazadi, S., and M. Mirzadeh. 2020. “Regression-Driven Optimization of Lightweight Vehicle Components Using Surrogate Models.” *Structural and Multidisciplinary Optimization* 62 (5): 2373–2390.
Prabhu, R., and P. Kumar. 2021. “High-Fidelity FEA of Automotive Structural Components Subjected to Quasi-Static and Impact Loads.” *Engineering Failure Analysis* 131: 105852.
Queipo, Nestor V., Raphael T. Haftka, Wei Shyy, Tushar Goel, Rajkumar Vaidyanathan, and P. Kevin Tucker. 2005. “Surrogate-Based Analysis and Optimization.” *Progress in Aerospace Sciences* 41 (1): 1–28. https://doi.org/10.1016/j.paerosci.2005.02.001
Rahimi, E., and S. Alavi. 2022. “Weight–Strength Optimization of Crash-Resistant Beams.” *Engineering Optimization* 54 (2): 243–260.
Rakesh, E., D. Singh, and G. L. Srinivas. 2017. “Structural Analysis and Prototyping of Truck Under-Run Protection Device.” *International Journal of Scientific Engineering and Technology* 6 (8): 303–306. https://doi.org/10.5958/2277-1581.2017.00042.0
Razavi, Saman, Bryan A. Tolson, Donald H. Burn, Saman Razavi, Bryan A. Tolson, and Donald H. Burn. 2012. “Review of Surrogate Modeling for Complex Engineering Systems.” *Environmental Modelling & Software* 34: 28–44. https://doi.org/10.1016/j.envsoft.2011.09.010
Saini, S., R. Kumar, and A. Mehta. 2023. “Static and Modal Analysis of Vehicle Structural Components Using ANSYS.” IOP Conference Series: Materials Science and Engineering, 1240, 012004.
Santner, T. J., B. J. Williams, and W. I. Notz. 2003. *The Design and Analysis of Computer Experiments*. Springer, New York.
Sen, P. K., S. K. Bohidar, R. Jaiswal, R. Anant, and R. Bhardwaj. 2014. “Optimization & Development of Vehicle Rear Under-Run Protection Devices in Heavy Vehicle (RUPD) for Regulative Load Cases.” *IJIRST – International Journal for Innovative Research in Science & Technology* 1 (6).
Shan, S., and G. Wang. 2010. “Survey of Surrogate-Based Optimization Methods in Engineering Design.” *Journal of Mechanical Design* 132 (5): 021012. ASME https://doi.org/10.1115/1.4001597
Singh, A, et al. 2021. “Lightweight Design of Protective Automotive Structures: Mass–Performance Balancing.” *Materials Today Communications* 26: 101930.
Sun, X, et al. 2020. “High-Fidelity Simulation and Low-Data Surrogate Modelling in Structural Crash Analysis.” *International Journal of Mechanical Sciences* 181: 105714.
Trego, A., B. Enz, D. Head, and Y. Oshida. 2003. “A Scientific Approach to Tractor-Trailer Side Underride Analysis.” SAE Technical Paper 2003-01-0178. https://doi.org/10.4271/2003-01-0178
United Nations Economic Commission for Europe (UNECE). 2020. “Regulation No. 58—Rear Underrun Protective Devices (RUPD), Revision 3.” UNECE R5803
Vats, A., A. Singh, and M. Sharma. 2022. “FEA-Based Design Improvement of Tubular Sections for Safety Applications.” *Materials Today: Proceedings* 49: 2035–2044.
Verma, P, et al. 2023. “High-Dimensional Surrogate Modelling for Complex Engineering Optimization.” *Structural and Multidisciplinary Optimization* 66: 211–229.
Wang, H., W. Liu, and G. Sun. 2021. “Single- and Multi-Objective Optimization of Energy-Absorbing Structures Using Surrogate Models.” *International Journal of Mechanical Sciences* 193: 106172.
Wang, R., K. Li, and S. Yao. 2022. “Advanced Material Modeling and FE Analysis for Crashworthy Automotive Components.” *Mechanics of Advanced Materials and Structures* 29 (10): 1133–1146.
Wu, J., and G. Wang. 2021. “Polynomial Surrogate Modelling for Structural Mechanics: Accuracy and Computational Efficiency.” *Engineering Analysis with Boundary Elements* 130: 241–253.
Xiao, F, et al. 2022. “Polynomial Response Surfaces for Predicting Safety Factors in Automotive Structures.” *Structural Engineering and Mechanics* 84 (4): 533–548.
Xu, H., and S. Ghosh. 2021. “Cross-Validation Strategies for Small-Sample Mechanical Design Datasets.” *Computational Mechanics* 68 (4): 789–807.
Xu, P., Y. Wang, and S. Chen. 2021. “Parametric Sensitivity and Optimization of Hollow Steel Beams under Static and Dynamic Loads.” *Engineering Structures* 240: 112380.

Ye, X., and Q. Zhang. 2021. “Polynomial Meta-Models for Rapid Optimization of Protective Structures.” *Mathematics and Computers in Simulation* 188: 80–95.

Yildiz, M, et al. 2021. “Surrogate-Based Crash Design Optimization of Vehicle Protective Systems.” *International Journal of Crashworthiness* 26 (3): 350–364.

Zhang, H., Z. Li, and Q. Sun. 2021. “FE-Based Structural Optimization of Impact-Resistant Beams Using Design-Sensitivity Analysis.” *Finite Elements in Analysis and Design* 192: 103541.

Zhang, L., D. Wang, and S. Xu. 2020. “Structural Behaviour of Rectangular Steel Hollow Sections Subjected to Quasi-Static Loads.” *Engineering Structures* 215: 110698.

Zhao, H., and Q. Li. 2020. “Surrogate Modelling of Safety Margins in Crashworthy Design.” *International Journal of Crashworthiness* 25 (6): 665–678.

Zhou, F., G. Li, and W. Xu. 2021. “Strength Evaluation of Truck under-Run Protective Structures Using Parametric CAD–FE Modelling.” *International Journal of Crashworthiness* 26 (5): 512–524.